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ANALYSIS OF METROPOLITAN HIGHWAY CAPACITY AND THE GROWTH IN VEHICLE MILES OF TRAVEL

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ABSTRACT

A number of recent studies have examined the hypothesis of induced travel in an attempt to quantify the phenomenon (Hansen & Huang, 1997; Noland, forthcoming). No study has yet attempted to adjust for potential simultaneity bias in the results. This study addresses this issue by the use of an instrumental variable (two stage least squares) approach. Metropolitan level data compiled by the Texas Transportation Institute for their annual congestion report is used in the analysis and urbanized land area is used as an instrument for lane miles of capacity. While this is not an ideal instrument, results still suggest a strong causal relationship but probably that most previous work has had an upward bias in the coefficient estimates. The effect of lane mile additions on VMT growth is forecast and found to account for about 15% of annual VMT growth with substantial variation between metropolitan areas. This effect appears to be closely correlated with percent growth in lane miles, suggesting that rapidly growing areas can attribute a greater share of their VMT growth to growth in lane miles.

INTRODUCTION

U.S. urban areas have experienced considerable growth in total vehicle miles of travel (VMT) over the last 30 years. This has been attributed to population growth, increases in total income, demographic changes such as decreased household size and increased female work force participation, and the decentralization of metropolitan areas. One factor that has often been mentioned is the pervasiveness of the highway network and its role in reducing the relative travel costs for motorized vehicles. Historically, this effect, described alternatively as induced travel, induced demand and/or latent demand, has been used by environmental advocates as an argument to stop or reduce highway construction programs. Yet, most transportation planners have been slow to accept the basic economic arguments of induced travel, generally arguing that travel demand is a derived demand dependent on economic activity.

Recent research has begun to shed new light on this issue. This has included the work of Hansen & Huang (1997), Noland (forthcoming), Goodwin (1996) and the SACTRA (1994) report of the UK Department of Transport. The latter was a policy document that asserted that induced travel effects should be taken into consideration in the assessment of new highway projects. The key policy issue is how these effects influence the benefit-cost ratio of transportation projects. If a project is assessed on its expected travel time reductions, then additional induced travel will degrade those estimated travel time benefits, making the project relatively less attractive. If traffic flow improvements are implemented to reduce emissions of pollutants, then induced travel could result in a faster than anticipated return to stop-and-go traffic and the consequences of more traffic emitting at a higher level of congestion. When long run impacts of accessibility changes are taken into account, the benefits of any specific project will also tend to accrue to current land owners who enjoy increased accessibility to their land. How these benefits work their way through the economy is yet to be truly assessed. However, the social costs of additional travel by single occupant vehicles have been well documented (see, for example, Delucchi, 1997).

While much recent research has begun to document these effects, some have disputed whether the causal relationships are being accurately estimated. One argument disputing induced demand is that highway planners have an inherent knowledge of where road facilities are needed and thus they expect them to fill up with traffic. This is, of course, circular reasoning, in that the expectation of a road project being completed will lay the groundwork for its eventual use, as economic actors, such as land developers, respond even before the project is complete. In addition, the *expectation* of economic actors that the government will respond by providing new capacity may make the need for new capacity self-fulfilling. Regardless of these arguments, the causality debate remains. This paper makes an attempt to estimate a two stage least squares regression using an instrumental variable to address this question.

For those who accept the notion that transportation infrastructure can have a behavioral impact, the question is how much of an effect. The SACTRA report (1994) found that travel forecasts average some 10 to 20 percent below actual results (over an unspecified time) because induced demand is not included. Goodwin (1996) found forecasts exceeded by an average of 5.7 percent over a one-year time period. Heanue (1998) found induced demand to be responsible for from 6 to 22 percent of total demand growth in Milwaukee from 1960 to 1990. Using state-level data for the United States from 1984 to 1996, Noland (forthcoming) found that induced demand contributed about 20 to 28 percent of total growth in VMT.

Travel demand elasticities from the literature, even for significantly different formulations of induced demand, appear to be developing some consensus in their results. The U.S. DOT (1997) utilizes an elasticity of VMT with respect to total travel costs of -0.8 for a five-year period and -1.0 for a twenty-year period in conducting its highway needs analysis. The U.K.'s SACTRA report (1994) found an elasticity of travel with respect to travel time ranging from -0.5 to -1.0, leading to official adoption of a national position requiring induced demand to be addressed in policy and project evaluation. Goodwin (1996) found a travel time elasticity of –0.28 in the short term and –0.57 in the long-term, with evaluation being conducted at the individual project level.

Among other recent studies, many addressed the elasticity of travel demand with respect to lane-miles of roadway (usually limited to just freeways and arterials). Hansen and Huang (1997) found elasticities of 0.9 in California metropolitan areas for a 4 to 5 year time period. Similarly, Johnston and Ceerla (1996) found elasticities of 0.6 to 0.9 over a three-year period in the same state. Noland (forthcoming) found short-term elasticities of 0.2 to 0.5 using data from 50 states, with corresponding long-term elasticities of 0.7 to 1.0.

It is important to bear in mind that different studies have looked at induced demand with different analytical techniques. The results are generally quite robust, though none of the studies are ideal due to the lack of accounting for simultaneity bias. Aggregate studies, however, provide only average results. In theory, if a road is not congested and capacity is added, then one would not expect any induced travel effect. One could hypothesize that induced demand will be a significant factor in only some projects. In other words, average and typical figures can easily fluctuate substantially up or down in an accurate reflection of local conditions. This issue is not raised to discredit individual analyses, all of which have contributed to the state of knowledge in the field. Rather, these examples give credence to the notion that induced demand is an important, but difficult to quantify aspect of the relationship between capacity expansions and travel demand, and that many results are very dramatically affected by the choice of analysis location, time period, and the level of aggregation. This paper attempts to address some of these issues while using aggregate data and finds (surprisingly) no measurable difference between congestion effects and hard to explain differences based on metropolitan area size. We do find that areas with a high rate of lane mile growth appear to induce relatively more of their VMT growth.

The paper is organized as follows. We begin with a brief introduction of the theory of induced travel and some of the controversy over the definition. This is followed by a description of the data used in the analysis. A section describing the methodologies is then presented, followed by the results of the analysis. A concluding section summarizing the results and the policy implications is also included.

THEORY OF INDUCED TRAVEL AND REGIONAL TRAVEL DEMAND MODELS

The concept of induced travel has been the focus of recent policy discussions in both the U.S. and abroad (especially in the U.K). However, precise definitions of the concept are not always clearly stated. For this research, induced travel is defined here simply as an increase in travel that occurs as a result of any increase in the capacity of the transportation system. Because of its easy availability and wide acceptance as a system measure, we use VMT as our metric to measure travel. Therefore one can think of induced travel as being the increase in system-wide travel measured as either annual or daily VMT. Vehicle-miles are the relevant measure rather than person-miles of travel primarily because of the social costs (e.g., congestion and environmental impacts) imposed by personal vehicle travel. An even broader definition could include all travel demand responses across modes.

The theory of induced travel is firmly based in microeconomics. It is essentially a demand response to a reduction in the price of a commodity, in this case the price of vehicle travel. The primary marginal cost of travel is the personal travel time invested to make a given trip. Therefore, when infrastructure changes decrease the travel time of a trip, and hence its cost, one would expect an increase in demand for travel. The detailed behavioral mechanisms include shifts to longer distance travel such as to destinations which previously were too distant, shifts from alternative modes such as transit, generation of new trips that were previously too costly to make, and long run impacts generated by changes in the relative access to economic and other activities . More detailed discussion of these issues, including the impacts under different elasticity assumptions, are provided in the SACTRA Report (1994), Arnott and Small (1995), Goodwin (1996), Mackie (1996), DeCorla-Souza and Cohen (1998), and Noland (forthcoming).

These shifts in supply and the corresponding demand response can also be translated into the language of regional travel demand models. In particular, both SACTRA (1994) and DeCorla-Souza and Cohen (1998) help trace through the elements of regional travel demand models to help theoretically separate out the different components of induced travel. Regional travel demand models are used to both assess the impacts of alternative highway and transit projects and are also used to forecast future emissions as required for the development of State Implementation Plans for meeting Clean Air Act requirements. However, these modeling systems are generally deficient in completely characterizing behavioral responses to added highway capacity.

Induced travel may be conceptualized as corresponding to the steps of the traditional four-step travel demand model. These include,

- **Trip generation** – New trips that previously did not occur;
- **Trip distribution** – Trips that now go to a different (further) destination;
- **Mode choice –** Trips diverted from other modes, including changes in vehicle occupancy;
- **Network assignment** – Trip diversions to the same destination using a longer, but now faster route.

Most modeling systems do not fully capture the impacts of changes in behavior in response to new capacity.

In addition, modeling systems are generally deficient in assessing the diversion of trips to alternative times of day. Re-scheduling of trips back to peak periods is generally the most visible demand response to a capacity enhancement, however this response does not actually result in an increase in net VMT and thus would not be included here within our definition as an induced travel effect. However, if a capacity expansion reduces the duration of peak travel times, additional trips could be generated during the now relatively less congested shoulder periods.

The four step regional transportation modeling process also does not address land use or development responses to increased accessibility. This is the long run response to changes in capacity (although the effects may materialize quickly if the completion of the facility is fully anticipated in advance by individual actors).

Although there have been some differences of opinion regarding which of these factors are actually induced demand and what exactly to call induced demand, for practical purposes these differences are moot. Almost all of the quantitative analyses that have been conducted by researchers are unable to differentiate the source of the additional traffic, and thus include the four cases (corresponding with the four steps of trip generation, trip distribution, mode choice, and network assignment) of traditional transportation modeling. Further, it should be noted that most studies, including this one, make no effort to segregate out or separately estimate the above elements. Rather, they are aggregated together by the nature of the data used here and can only be addressed together as a combined figure for the increase in VMT.

DATA DESCRIPTION AND SOURCES

A data set from the Texas Transportation Institute (TTI) was used in this analysis. This data is used in Schrank & Lomax (1997) for TTI's annual report on congestion. The most recent database includes metropolitan level data from 70 urbanized areas from 1982 through 1996.

The TTI data was cross-checked with data obtained from the Federal Highway Administration's (FHWA) Highway Performance Monitoring System (HPMS), and it was concluded that TTI data reported for freeway and arterial roadways is consistent with FHWA data. However, there were minor problems with some of the data reported for total centerline miles for all roadway systems in several of the metropolitan areas. Efforts to refine the centerline data through either

Metropolitan Planning Organizations or State Departments of Transportation appeared that they would be extremely burdensome, and TTI confirmed that they found only freeway and arterial data could be consistently obtained. Therefore, only the freeway and arterial data for VMT and lane-miles were used in this analysis. This is consistent with most other studies, both because of the unreliability of VMT data on minor roads and because they are thought to have a much smaller role in induced demand.

In addition to data on VMT and lane-miles, TTI also provided data on metropolitan area population, licensed drivers, urbanized land area, and state level fuel costs. These data were cross-checked against other sources and for internal consistency, and were found to be of good quality. Annual data on per capita income at the state level were also collected and used in this analysis.

METHODOLOGY

The data on metropolitan areas was analyzed using a cross-sectional time series modeling approach. This includes the use of fixed effects across both urbanized areas and time. The power of the fixed effects method is that one need not have information on all factors that may influence the dependent variable (for a good background text on the subject see Johnston & Dinardo, 1997). Many of the demographic factors that have been cited as influencing VMT growth, such as increased women in the labor force, are highly correlated with population growth or do not have data available at the cross-sectional unit of analysis. Another issue is the potential for simultaneity bias in the data. For example, if VMT growth were to be a determinant of lane mile growth, then the estimation may not be efficient. Fixed effects estimation can help minimize, but not eliminate simultaneity bias. An instrumental variable (two stage least squares) approach is used to address this issue.

Models of the following general form were estimated:

$$\log\left(VMT / PC_{it}\right) = c + \boldsymbol{\alpha}_i + \boldsymbol{\tau}_t + \sum_k \boldsymbol{\beta}^k \log\left(X_{it}^{k}\right) + \boldsymbol{\lambda} \log\left(LM / PC_{itl}\right) + \boldsymbol{\varepsilon}_{it}$$

The parameters are defined as:

VMT / PC_{it} = VMT per capita in metropolitan area *i*, for year *t*.

c = constant term

$\boldsymbol{\alpha}_i$ = fixed effect for metropolitan area *i*, to be estimated

τ_t = fixed effect for year *t*, to be estimated

$\boldsymbol{b}^k$ = coefficients to be estimated (for demographic and other parameters)

$\boldsymbol{l}$ = coefficient to be estimated for lane mile (LM) parameter

X_{it}^{k} = value of demographic and other variables for metropolitan area, *i*, and time, *t*.

LM / PC_{it} = proxy for cost of travel time (lane miles per capita) by metropolitan area, *i*, for year, *t*.

$\boldsymbol{e}_{it}$ = random error term

Hansen and Huang (1997) estimated a similar model using data on California counties and metropolitan areas. Noland (forthcoming) also estimated a model without year effects using state data.

An instrumental variable was specified as:

$$\log\left(LM / PC_{itl}\right) = c + \boldsymbol{a}_i + \boldsymbol{t}_t + \boldsymbol{k} IV_{it} + \sum_k \boldsymbol{b}^k \log\left(X_{it}^{k}\right) + \boldsymbol{e}_{it}$$

where IV_{it} is the instrument, specified both across urbanized areas and time.

The models are estimated with VMT per capita on freeways and arterials as the dependent variable. Noland (forthcoming) used both VMT per capita and total VMT (excluding local roads) and found no substantive difference in results. The key independent variable is the lane miles of freeway and arterials (per capita) for each metropolitan area by year. These categories of roads represent approximately 64% of total VMT for the metropolitan areas in the sample. About 28% of urbanized lane miles nationwide are freeways and arterials. While a more comprehensive analysis would include all road capacity, the metropolitan data on local and collector lane miles were not sufficiently accurate for this analysis. However, capacity expansions of freeways and arterials tend to be more controversial and have greater regional impact than minor roads and thus the analysis here provides useful information on their aggregate impact. The use of lane miles per capita serves as a proxy for congestion or travel time and therefore for the generalized cost of travel. If lane miles are held constant, but population increases, then the variable will decrease in size (i.e., the cost of travel will increase).

Other variables also affect VMT per capita and are controlled for in the analysis. These include fuel cost, population density of the metropolitan area, and real per capita income. Fuel cost and per capita income were available only at the state level. Population density included not only changes in total population but also expansion of the metropolitan area over time. Other unmeasured influences on VMT could include changes in female participation in the work force, extent and/or existence of transit systems, and other factors that may vary across urbanized areas and over time. As mentioned previously, the use of fixed effects controls for other variables that may have an effect on VMT.

Between 1982 and 1996 the annual percent change in these variables for each metropolitan area is shown in Table 1. The growth in lane miles shows a large amount of variance, ranging from an annual rate of over 6% for Tucson, Arizona to less than 1% for the Albany, New York area. Lane miles per capita decreased by over 3% per year in the Las Vegas area (probably due to a high annual population growth rate). Tucson also had the highest rate of growth in lane miles per capita, about 3.5% annually.

Population density is generally decreasing for most metropolitan areas, ranging from an annual decrease of over 3.3% per year for the Bakersfield, California area to an increase of about 1.6% per year in Atlanta, Georgia. These changes depend on the relative growth in population compared to growth in urbanized land area (i.e., sprawl). The latter has grown as much as 9.2% annually in the Las Vegas, Nevada metropolitan area.

Growth in per capita income ranges between about 1.0% and 2.5% annually. Fuel costs (in real terms) have generally decreased a fraction of a percent each year, with much of this decrease coming between 1982 and 1985.

RESULTS

Results for a number of estimations are presented in Table 2. T-statistics are shown in parentheses below the coefficients. A value above 1.96 gives at least a 95% level of confidence in the coefficient estimate. Fixed effect constants are not shown in the tables for brevity. Lane mile coefficients can be read as elasticities of VMT per capita with respect to lane miles per capita due to the logarithmic specification used. The population denominator drops out of the calculation giving elasticities of VMT with respect to lane miles. Since the model is estimated as a log-linear model, elasticities are defined as,

$$I = \frac{\partial \log(VMT)}{\partial \log(LM)} = \frac{LM}{VMT} \cdot \frac{\partial(VMT)}{\partial(LM)}$$

Model (A) shows a lane mile elasticity of 0.655. This can be interpreted as showing that VMT (on freeways and arterials) will increase by 0.655% for every 1% increase in lane miles of freeways and arterials. Per capita income shows a significant and positive effect, as would be expected. Fuel cost is negative but not significant. Increased population density also results in a statistically significant decrease in VMT. Model (C) shows similar results when the population density variable is omitted. The total fit of the model (as measured by the R^2) is marginally decreased (from 0.851 to 0.841).

Model (B) is similar to model (A) but includes a time series (year) variable rather than fixed effects across years. The results are essentially the same as in the model with year fixed effects, except the fuel cost coefficient is now statistically significant. The year variable shows a positive and statistically significant coefficient implying some increase over time in VMT per capita independent of the other variables in the model.

Short run and long run elasticities can be analyzed using a distributed lag model. The dependent variable (VMT per capita), lagged by one year, is included as an independent variable in the estimation. The coefficients on the independent variables are short run lags while the long run lags can be calculated as follows:

$$h = \frac{l}{1-g}$$

The adjustment parameter, γ, is the coefficient on the lagged VMT variable, while λ is the short run elasticity (Johnston, 1984). Estimating with a distributed lag assumes that the lag structure is exponential. Alternatively one could attempt to specify a lag structure for the model but there is no reason to believe that any specific structure is the correct specification. An exponential distribution assumes that immediate short run impacts are the greatest and long term impacts diminish over time at an exponential rate. This seems a reasonable assumption for the behavioral mechanisms being modeled. Another assumption of the distributed lag model is that all the independent variables have the same lag structure, thus the coefficients on the other independent variables in model (D) are all short run elasticities. Long run elasticities are shown at the bottom of Table 2.

The results for model (D) clearly show that lane mile elasticities are smaller in the short run (0.284) and quite large in the long run (0.904). This is consistent with other research. For example, at the state level, Noland (forthcoming) uses a distributed lag model to estimate short run elasticities of about 0.3 to 0.5 and long run elasticities of 0.7 to 1.0. Both are similar to the results here.

An additional source of error in the estimations is potential autocorrelation in the error terms. The models were also run using a generalized least square procedure adjusted for serial correlation. Coefficients were found not to vary in magnitude.

While these models show very robust results for the elasticity of VMT per capita with respect to lane miles per capita, the use of a Durbin-Wu-Hausman test for endogeneity suggests that the coefficients are not consistent. Therefore it is more appropriate to use an instrumental variable approach. One possible variable is to use the total urbanized land area for each metropolitan area which tends to grow over time. This variable shows relatively low correlation with VMT per capita of 0.423, but is obviously not completely orthogonal. Its direct correlation with lane miles per capita is low (-0.151), however results of a fixed effects regression of lane miles per capita (Table 3, Model 3-A) shows that the variable is statistically significant and has the expected sign. As urbanized land area increases, lane miles per capita decreases implying that less capacity is being added than would be proportional to regional growth. Increases in per capita income increase the level of lane miles per capita and increased population density decreases it. This result is also shown with a year variable in model 3-B.

The population density variable is equal to population divided by urbanized land area, therefore there is some interaction between this variable and the main instrument. The actual elasticity of urbanized land area, with respect to lane miles per capita, should be reduced by the elasticity of the population density. This would result in a small positive value for this variable. This effect is due to the following relationship,

$$LM \big/ P = \left(\frac{P}{A}\right)^{a} \cdot (A)^{b} \cdot (X_k)^{q} = \left(P^{a}\right) \cdot (A)^{b-a} \cdot (X_k)^{q}$$

LM is lane miles, P is the population, A is urbanized land area and X_k is other variables in the equation. The actual elasticity for urbanized land area reduces to β-α, the difference between the estimated elasticities for population density and urbanized land area. Column (C) shows results when population density is omitted from the estimation to avoid this problem. The urbanized land area variable remains negative and significant while the coefficient on per capita income increases. Column (D) shows the same estimate but with a variable for years, rather than fixed effects for individual years. Results in model 3-D are basically the same as in model 3-C.

An alternative instrument might be the inverse of the population density (area / population). This variable has a low correlation with VMT per capita (0.376) and higher correlation with lane miles per capita (0.556). This variable also has a relatively simple interpretation as it represents the increase in lane miles associated with increases in urbanized land area, holding population constant. Column (E) estimates a lane mile model with this variable and shows a significant effect and indicates that growth in lane miles is less for proportional increases in urbanized land area. Note that the coefficient on per capita income also increases in size relative to model 3-A and similar to size for model 3-C.

Both of these instruments are used in a two stage least squares estimation. The urbanized land area is used both with and without population density in the model. Results are shown in Table 4. The first model with urbanized land area as an instrument and including population density in the model shows very similar results to model 2-A. The coefficent on lane miles per capita increases slightly from 0.655 to 0.760 suggesting a strong causal relationship between lane miles per capita and VMT per capita though this result should be caveated by the less than ideal correlation between the instrument and lane miles per capita. The other coefficients are also similar in value to the model estimated previously. Model 2-B is also similar but includes a year variable rather than fixed effects across years. Column C drops the population density variable. In this model the lane mile per capita coefficient decreases to 0.289 while the coefficient on per capita income increases to 0.557. This can be compared to the model in column C of Table 2 which has a higher elasticity on the lane mile coefficient of 0.683. Likewise the model in column D can be compared to the model in column D of Table 2 with a lane mile coefficient of 0.277 versus 0.647.

The alternative instrument of population divided by urbanized land area does not give a clear result. The coefficient on lane miles is significant and much larger than the coefficients estimated previously. The per capita income coefficient also becomes negative and insignificant while the fuel coefficient becomes positive and significant. Both of these are counterintuitive results which suggests that some unexpected interactions are occurring in the estimation. Again, the less than ideal correlations of the instrument may help explain the large shift in this coefficient value. Despite the limitations of a less than ideal instrument, these results still are suggestive that there is a causal relationship between growth in lane miles and VMT.

RELATIVE CONTRIBUTIONS TO VMT GROWTH

The impact of lane mile growth on total VMT is forecasted out to 2010 for each metropolitan area. Note that these VMT figures are only for freeways and arterials (which have experienced faster VMT growth than other urban roads; Schrank and Lomax (1997)). Results are presented in Table 5 and are forecast using three of the models previously estimated. These are the model 2-B, and two of the instrumental variable models, 4-B and 4-D. The first three columns show the forecast annualized growth rate of VMT assuming that the growth rates in all the independent variables, for each metropolitan area, remain the same as the growth rates between 1982 and 1996. Average growth for all the metropolitan areas is forecast to be 2.99% using model 2-B, and 3.90% and 3.85% using the two instrumental variable models. The latter two models show a higher annual growth rate as they are capturing some of the simultaneity between VMT growth and lane mile growth.

These results are compared to a forecast with no growth in lane miles between 1996 and 2010. Total annualized growth in average VMT is reduced to 1.64% per year using model 2-B, 2.33% per year using model 4-B and to 3.28% per year using model 4-D. The relative reduction in growth when no lane miles are constructed is defined as the "induced travel effect" or the contribution to VMT growth of lane miles. These results are shown in Table 6. Model 2-B results in an induced travel effect of 45%, while the two instrumental variable models range from a high of 40% for model 4-B to 15% using model 4-D.

These results can be compared to the induced travel effect of 20-28% reported in Noland (forthcoming) and the 6-22% reported by Heanue (1998). Both these were calculated without any explicit correction for simultaneity bias, though Heanue's upper bound was based upon the work of Goodwin (1997) which estimated travel time elasticities using a different methodology. The 15% to 40% value calculated using instrumental variable models covers this range.

Table 6 also provides details on the induced travel effect for each metropolitan area. It is not clear why different urbanized areas have different levels of the induced travel effect. If we focus on the results from model 4-D we see that the effect ranges from a low of 6.41% for Fresno, California up to a high of 34.29% for Louisville, Kentucky. Model 4-B ranges from a low of 15.32% for the Buffalo-Niagara Falls, New York area to a high of 65.59% for the Austin, Texas area. It is not clear why this variation occurs.

One potential source of variation is the relative growth in lane miles used in the forecasts. A simple logarithmic regression of the induced travel effect versus the annual growth in lane miles shows a strong correlation. The resulting equations using models 4-B and 4-D are:

$IE = 1.19 + 0.54LMG$ *(based on Model 4-B)*

$IE = 0.85 + 0.70LMG$ *(based on Model 4-D)*

Where *IE* = the logarithm of the induced travel effect and *LMG* = the logarithm of lane mile growth. The coefficient is highly significant and the regression have an R^2 of 0.793 and 0.627 respectively. This relationship implies that for every 1% growth in the growth of lane miles there will between 0.54 to 0.70 percent growth in the induced travel effect. Or put another way, those areas with high lane mile growth, relative to their current base, will have higher VMT growth because of the lane mile growth. This relationship is shown graphically in Figure 1 for both of the instrumental variable models.

These results do not appear to be affected by either existing congestion or the relative size of the metropolitan area. Disaggregation of the VMT forecasts into large, medium, and small urbanized areas, and subsequent calculation of the average induced travel effect showed no substantive difference. Using model 4-D it was about 14% for large areas, 19% for medium areas, and 15% for smaller metropolitan areas. Model 4-B resulted in estimates of 39%, 49% and 40% for large, medium and small areas respectively. When adjusted by the relative congestion index (as defined in Schrank & Lomax, 1997) the results are similar. Model 4-B results in high congestion areas having an induced travel effect of about 15% relative to 16% for areas with lower congestion indexes. The results for model 4-B are 40% and 43% respectively.

These results imply that, in general, metropolitan size and/or congestion levels do not seem to effect the relative strength of the induced travel effect. Metropolitan areas that invest in large percent increases in road capacity relative to their current base appear to generate the most additional VMT. This result may represent a sprawl effect as much of this new capacity would be built to access newly developing land.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper has provided an estimate of the impact of lane mile additions on VMT growth using an instrumental variable procedure to correct for simultaneity bias. While the instruments selected were not ideal the results are highly suggestive of a causal linkage. Recent literature on this topic, while not accounting for simultaneity bias also offers strong evidence that the induced travel hypothesis cannot be rejected. In addition the impact of lane mile additions on VMT growth appears to be greater in urbanized areas with larger percent increases in total capacity. This may be evidence for a strong sprawl inducing impact of large increases in lane mile capacity relative to the existing infrastructure.

The implications for U.S. transportation policy of induced travel effects have not been fully absorbed. Recognition of these impacts implies that the benefits of new highway construction are less than would be calculated from a static analysis that included no induced travel impacts.

To a large extent, transportation policy in the U.S. has been focused on maintaining traffic flows and reducing congestion. Under current travel behavior patterns, induced travel effects strongly imply that pursuit of congestion reduction by building more capacity will have short-lived benefits. Providing more people with the ability to travel, even if under congested conditions, does provide some benefits. However, these must be weighed against the social costs of increased vehicle usage. Mobility and accessibility benefits can be provided in other ways that do not incur as large of an increase in these social costs (including adverse health effects from increased emissions and injuries and fatalities from crashes).

Since passage of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) and its successor, the Transportation Equity Act for the 21st Century of 1998 (TEA-21), U.S. transportation policy has recognized the need for greater balance in the funding of alternatives to motor vehicle travel. TEA-21 included about a 40% increase in total federal funding of projects. While the total funding passed in 1998 increased the fraction of the total that non-highway (primarily transit) projects receive, it still provided a massive increase in spending for traditional highway expansion projects. In addition, over 1800 additional projects (primarily highway projects) were earmarked by the Congress. Clearly, this level of funding creates a bias for continued pursuit of the types of projects that have been historically less effective than expected at reducing congestion.

The linkage between increasing highway capacity and changes in land use patterns is increasingly being recognized by policy makers. The efficiency and long-term sustainability of urban areas is threatened by development patterns that are resource intensive and generate excessive (and auto dependent) travel patterns. Recognizing the links between highway capacity expansions, the difficulties in reducing congestion through these projects, and their potential sprawl-inducing impacts, will require a radical change in federal transportation policy if a more sustainable outcome is desired.

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DISCLAIMER

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Table 1

Annual Growth Rates of Key Indicators Between 1982 - 1996

	Lane Miles - Freeways and Arterials	*VMT - Freeways and Arterials*	*Lane Miles per capita - Freeways and Arterials*	*VMT per capita - Freeways and Arterials*	*Population*	*Urbanized Land Area*	*Population Density*	*Fuel Cost*	*Income per capita*
Albany-Schenectady-Troy	0.59%	4.03%	0.67%	4.11%	-0.07%	0.20%	-0.26%	0.11%	2.41%
Albuquerque	3.25%	4.93%	1.49%	3.14%	1.74%	1.94%	-0.21%	-0.21%	1.46%
Allentown-Bethlehem-Easton	2.30%	3.25%	1.21%	2.14%	1.08%	2.94%	-1.80%	-0.17%	2.12%
Atlanta	3.84%	5.75%	0.71%	2.56%	3.10%	1.45%	1.63%	-1.26%	2.73%
Austin	5.32%	6.84%	1.70%	3.17%	3.56%	1.98%	1.55%	-0.35%	1.20%
Bakersfield	3.20%	4.81%	-0.15%	1.41%	3.35%	6.98%	-3.38%	-0.83%	1.20%
Baltimore	1.88%	3.93%	0.20%	2.22%	1.67%	3.62%	-1.88%	-0.43%	2.18%
Beaumont	1.58%	2.28%	0.16%	0.86%	1.41%	1.52%	-0.11%	-0.35%	1.20%
Boston	0.95%	1.97%	0.56%	1.57%	0.39%	1.72%	-1.30%	0.00%	2.70%
Boulder	2.24%	4.02%	0.27%	2.02%	1.96%	5.08%	-2.96%	0.11%	1.68%
Brownsville	1.84%	4.31%	-1.06%	1.33%	2.94%	2.94%	0.00%	-0.35%	1.20%
Buffalo-Niagara Falls	0.61%	2.05%	0.61%	2.05%	0.00%	3.04%	-2.95%	0.11%	2.41%
Charlotte	2.76%	5.27%	-0.76%	1.66%	3.54%	3.41%	0.12%	-0.78%	2.86%
Chicago-Northwestern IN	2.76%	4.27%	2.00%	3.50%	0.74%	2.65%	-1.86%	0.21%	2.09%
Cincinnati	1.37%	3.46%	0.56%	2.63%	0.81%	1.07%	-0.27%	-0.43%	2.01%
Cleveland	1.17%	3.20%	0.73%	2.76%	0.44%	1.54%	-1.09%	-0.43%	2.01%
Colorado Springs	1.86%	4.14%	-0.70%	1.52%	2.58%	3.28%	-0.68%	0.11%	1.68%
Columbus	1.37%	4.27%	-0.00%	2.86%	1.37%	3.21%	-1.80%	-0.43%	2.01%
Corpus Christi	2.40%	3.91%	0.84%	2.33%	1.55%	0.98%	0.56%	-0.35%	1.20%
Dallas	1.59%	3.50%	-0.10%	1.78%	1.69%	1.09%	0.60%	-0.35%	1.20%
Denver	1.16%	3.04%	-0.78%	1.06%	1.95%	1.01%	0.95%	0.11%	1.68%
Detroit	1.67%	2.78%	1.75%	2.86%	-0.08%	1.29%	-1.35%	-0.22%	2.36%
El Paso	1.30%	2.80%	-0.82%	0.65%	2.14%	3.26%	-1.09%	-0.35%	1.20%
Eugene-Springfield	0.96%	3.96%	0.24%	3.22%	0.72%	1.96%	-1.22%	0.00%	2.18%
Fort Worth	2.05%	3.90%	0.88%	2.71%	1.16%	1.22%	-0.05%	-0.35%	1.20%
Fresno	1.06%	2.77%	-2.00%	-0.34%	3.11%	4.08%	-0.92%	-0.83%	1.20%
Ft. Lauderdale-Hollywood-Pompano Bch	2.17%	3.34%	-0.23%	0.91%	2.40%	2.64%	-0.23%	-0.27%	1.97%
Harrisburg	2.36%	4.33%	1.37%	3.32%	0.97%	3.95%	-2.86%	-0.17%	2.12%
Hartford-Middletown	2.10%	3.80%	1.26%	2.94%	0.84%	0.49%	0.35%	0.61%	2.70%
Honolulu	1.86%	3.30%	0.33%	1.74%	1.53%	3.45%	-1.86%	1.52%	2.02%
Houston	2.97%	3.15%	1.20%	1.37%	1.75%	0.67%	1.06%	-0.35%	1.20%

Indianapolis	1.95%	4.84%	0.86%	3.72%	1.08%	1.11%	-0.03%	-0.50%	2.21%
Jacksonville	2.80%	3.64%	0.71%	1.53%	2.08%	1.61%	0.44%	-0.27%	1.97%
Kansas City	1.94%	4.26%	0.45%	2.73%	1.49%	2.43%	-0.92%	-0.12%	2.01%
Laredo	4.69%	6.85%	1.33%	3.42%	3.32%	4.29%	-0.93%	-0.35%	1.20%
Las Vegas	2.94%	7.67%	-3.27%	1.17%	6.42%	9.22%	-2.56%	0.42%	1.84%
Los Angeles	1.17%	3.08%	-0.34%	1.54%	1.52%	1.47%	0.05%	-0.83%	1.20%
Louisville	2.80%	5.06%	2.21%	4.45%	0.58%	0.66%	-0.08%	-0.39%	2.01%
Memphis	3.06%	4.66%	1.36%	2.93%	1.68%	1.89%	-0.20%	-0.23%	2.79%
Miami-Hialeah	1.85%	3.48%	0.62%	2.23%	1.22%	1.99%	-0.76%	-0.27%	1.97%
Milwaukee	1.75%	2.92%	1.52%	2.68%	0.23%	0.13%	0.10%	0.00%	1.95%
Minneapolis-St. Paul	2.24%	4.86%	0.42%	2.99%	1.81%	2.73%	-0.90%	-0.05%	2.31%
Nashville	3.09%	5.80%	1.46%	4.13%	1.61%	3.13%	-1.46%	-0.23%	2.79%
New Orleans	2.13%	2.85%	1.89%	2.62%	0.23%	0.61%	-0.37%	-0.51%	1.24%
New York-Northeastern NJ	1.28%	2.42%	1.07%	2.21%	0.21%	0.69%	-0.48%	0.11%	2.41%
Norfolk	2.11%	3.88%	0.15%	1.89%	1.96%	0.35%	1.59%	-0.73%	2.19%
Oklahoma City	2.06%	3.20%	-1.00%	0.11%	3.09%	3.17%	-0.07%	-0.83%	0.43%
Omaha	1.69%	4.26%	0.94%	3.49%	0.75%	1.03%	-0.28%	0.28%	1.96%
Orlando	2.86%	4.85%	-1.09%	0.83%	3.99%	2.20%	1.76%	-0.27%	1.97%
Philadelphia	1.83%	2.51%	-0.02%	0.64%	1.86%	3.19%	-1.29%	-0.17%	2.12%
Phoenix	3.29%	4.26%	-0.28%	0.66%	3.58%	4.94%	-1.30%	-0.49%	1.74%
Pittsburgh	2.10%	3.11%	1.63%	2.64%	0.46%	2.38%	-1.88%	-0.17%	2.12%
Portland-Vancouver	3.05%	5.02%	1.35%	3.28%	1.68%	2.13%	-0.43%	0.00%	2.18%
Providence-Pawtucket	3.13%	3.67%	2.49%	3.02%	0.62%	1.04%	-0.42%	0.05%	2.17%
Rochester	1.99%	4.85%	2.22%	5.08%	-0.23%	1.04%	-1.25%	0.11%	2.41%
Sacramento	2.72%	4.53%	-0.13%	1.64%	2.85%	2.49%	0.35%	-0.83%	1.20%
Salem	1.31%	3.85%	0.46%	2.98%	0.84%	0.49%	0.35%	0.00%	2.18%
Salt Lake City	3.26%	6.09%	1.25%	4.03%	1.98%	2.30%	-0.31%	-0.22%	2.15%
San Antonio	2.02%	4.15%	0.19%	2.27%	1.83%	1.23%	0.59%	-0.35%	1.20%
San Bernardino-Riverside	2.46%	2.52%	-0.11%	-0.06%	2.58%	1.89%	0.67%	-0.83%	1.20%
San Diego	1.42%	4.44%	-1.19%	1.75%	2.64%	1.49%	1.14%	-0.83%	1.20%
San Francisco-Oakland	1.35%	2.98%	0.14%	1.76%	1.20%	2.19%	-0.97%	-0.83%	1.20%
San Jose	1.45%	3.31%	-0.59%	1.23%	2.05%	1.15%	0.90%	-0.83%	1.20%
Seattle-Everett	1.42%	3.39%	-0.76%	1.17%	2.19%	1.58%	0.59%	0.22%	1.88%
Spokane	1.22%	2.12%	0.01%	0.91%	1.20%	0.68%	0.51%	0.22%	1.88%
St. Louis	2.12%	4.02%	1.48%	3.37%	0.63%	1.93%	-1.28%	-0.12%	2.01%
Tacoma	1.14%	3.94%	-1.28%	1.44%	2.46%	2.22%	0.23%	0.22%	1.88%
Tampa	4.01%	5.19%	0.96%	2.10%	3.03%	2.80%	0.21%	-0.27%	1.97%
Tucson	6.14%	6.92%	3.51%	4.26%	2.55%	4.56%	-1.93%	-0.49%	1.74%

Washington DC	2.53%	4.20%	0.73%	2.37%	1.79%	1.65%	0.14%	-0.73%	2.84%

Table 2
Regression Models

	(A)	(B)	(C)	(D)
LN(vmt per capita)	With fixed effects	Fixed effects on metro areas with year variable	With fixed effects	Distributed lag, with fixed effects
LN(lane miles per capita)	0.655 (27.491)	0.647 (27.568)	0.683 (28.081)	0.284 (16.088)
LN(vmt/pc lagged one year)				0.686 (38.797)
LN(per capita income)	0.354 (7.288)	0.377 (8.727)	0.393 (7.876)	0.091 (2.782)
LN(fuel cost)	-0.017 (-0.642)	-0.053 (-4.119)	0.014 (0.526)	-0.025 (-1.571)
LN(population density)	-0.174 (-7.952)	-0.176 (-8.159)		-0.077 (-5.379)
Year		0.011 (13.875)		
Constant	0.082 (0.155)	-21.923 (-18.129)	-1.664 (-3.352)	0.385 (-1.116)
N	1050	1050	1050	980
Adjusted R^2	0.851	0.851	0.841	0.940
Long run elasticities				
Lane miles				0.904
Per capita income				0.290
Fuel cost				-0.080
Population density				-0.245

Table 3
Estimated Model with Lane Miles per capita as Dependent Variable

	(A)	(B)	(C)	(D)	(E)
LN(lane miles per capita)	With fixed effects	Fixed effects on metro areas with year variable	With fixed effects	Fixed effects on metro areas with year variable	With fixed effects
LN(urbanized land area)	-0.629 (-21.417)	-0.635 (-21.676)	-0.209 (-9.00)	-0.204 (-8.745)	
LN(land area / population)					0.122 (4.190)
LN(per capita income)	0.134 (2.464)	0.108 (2.263)	0.387 (6.201)	0.323 (5.854)	0.371 (5.718)
LN(population density)	-0.689 (-19.295)	-0.703 (-19.874)			
Year		0.013 (11.426)		0.002 (2.005)	
Constant	8.278 (10.768)	-16.796 (-10.305)	-2.130 (-3.304)	-1.560 (-2.796)	-2.318 (-3.244)
N	1050	1050	1050	1050	1050
Adjusted R^2	0.411	0.849	0.183	0.159	0.130

Table 4
Instrumental Variable (2 Stage Least Squares) Regressions

	(A)	(B)	(C)	(D)	(E)
LN(vmt per capita)	Insrument = LN(area)	Insrument = LN(area) with year variable	Insrument = LN(area)	Insrument = LN(area) with year variable	Instrument = LN(population / area)
LN(lane miles per capita)	0.760 (18.092)	0.758 (18.230)	0.289 (2.873)	0.277 (2.746)	1.944 (6.035)
LN(per capita income)	0.315 (6.198)	0.344 (7.657)	0.557 (8.051)	0.552 (9.191)	-0.135 (-0.798)
LN(fuel cost)	-0.005 (-0.179)	-0.052 (-4.032)	-0.023 (-0.713)	-0.045 (-3.025)	0.135 (2.186)
Year		0.011 (13.966)		0.010 (10.411)	
LN(population density)	-0.160 (-7.077)	-0.161 (-7.213)			
Constant	0.476 (0.887)	-22.085 (-17.900)	-3.193 (-4.701)	-22.867 (-16.199)	3.595 (2.224)
N	1050	1050	1050	1050	1050
Adjusted R^2	0.975	0.975	0.967	0.967	0.902

Table 5: Forecasted Annual growth rate in VMT using Models 2-B, 4-B, and 4-D.

Metropolitan area	*Forecast using reduced form model 2-B. Annual growth rate in VMT (on freeways & arterials), assuming current growth trends*	*Forecast using Instrumental Variable model 4-B. Aannual growth rate in VMT (on freeways & arterials), assuming current growth trends*	*Forecast using Instrumental Variable model 4-D. Aannual growth rate in VMT (on freeways & arterials), assuming current growth trends*	*Forecast using reduced form model 2-B. Forecast annual growth rate in VMT (on freeways & arterials), with no growth in lane miles*	*Forecast using Instrumental Variable model 4-B. Forecast annual growth rate in VMT (on freeways & arterials), with no growth in lane miles*	*Forecast using Instrumental Variable model 4-D. Forecast annual growth rate in VMT (on freeways & arterials), with no growth in lane miles*
Albany-Schenectady-Troy	3.53%	1.81%	1.97%	3.14%	1.35%	1.80%
Albuquerque	4.17%	4.70%	3.73%	2.03%	2.19%	2.82%
Allentown-Bethlehem-Easton	5.00%	4.64%	3.80%	3.46%	2.85%	3.15%
Atlanta	3.60%	5.63%	6.11%	1.11%	2.65%	5.01%
Austin	5.17%	6.24%	5.37%	1.70%	2.15%	3.87%
Bakersfield	8.95%	5.78%	5.21%	6.75%	3.28%	4.29%
Baltimore	3.41%	4.06%	3.87%	2.17%	2.61%	3.33%
Beaumont	5.70%	3.62%	3.77%	4.63%	2.39%	3.32%
Boston	3.72%	3.70%	3.64%	3.08%	2.96%	3.36%
Boulder	6.75%	4.70%	4.06%	5.23%	2.96%	3.42%
Brownsville	7.46%	3.29%	4.52%	6.19%	1.87%	3.99%
Buffalo-Niagara Falls	5.61%	3.07%	2.67%	5.20%	2.60%	2.49%
Charlotte	5.15%	4.85%	6.12%	3.31%	2.71%	5.33%
Chicago-Northwestern IN	3.84%	4.73%	3.14%	2.03%	2.59%	2.37%
Cincinnati	2.09%	2.77%	2.79%	1.19%	1.71%	2.40%
Cleveland	2.56%	2.98%	2.52%	1.79%	2.07%	2.19%
Colorado Springs	6.79%	4.23%	5.07%	5.53%	2.79%	4.54%
Columbus	2.56%	3.24%	3.26%	1.66%	2.18%	2.87%
Corpus Christi	4.77%	3.38%	2.98%	3.18%	1.54%	2.31%
Dallas	2.20%	3.31%	3.79%	1.16%	2.08%	3.33%
Denver	2.82%	2.91%	4.04%	2.06%	2.01%	3.71%
Detroit	2.26%	3.40%	2.20%	1.17%	2.11%	1.73%
El Paso	4.86%	3.59%	4.26%	3.99%	2.58%	3.89%
Eugene-Springfield	3.86%	2.16%	2.83%	3.22%	1.42%	2.56%
Fort Worth	2.72%	3.28%	2.77%	1.38%	1.70%	2.20%
Fresno	5.76%	3.43%	4.74%	5.05%	2.61%	4.44%
Ft. Laud.-Hollywood-Pomp. Bch	4.25%	4.13%	4.67%	2.81%	2.45%	4.05%
Harrisburg	3.88%	4.37%	3.36%	2.32%	2.54%	2.70%
Hartford-Middletown	4.19%	4.20%	4.04%	2.79%	2.57%	3.44%
Honolulu	2.38%	4.29%	3.78%	1.17%	2.84%	3.25%
Houston	2.75%	4.58%	4.10%	0.82%	2.29%	3.26%
Indianapolis	2.54%	3.04%	2.70%	1.26%	1.54%	2.15%

Jacksonville	4.92%	4.61%	4.51%	3.06%	2.44%	3.71%
Kansas City	3.58%	3.62%	3.49%	2.30%	2.12%	2.94%
Laredo	8.87%	5.66%	4.66%	5.69%	2.05%	3.34%
Las Vegas	6.25%	5.14%	7.65%	4.27%	2.86%	6.79%
Los Angeles	-0.01%	2.9399%	3.38%	-0.76%	2.04%	3.05%
Louisville	2.37%	3.56%	2.27%	0.55%	1.41%	1.49%
Memphis	5.07%	4.62%	4.42%	3.03%	2.26%	3.55%
Miami-Hialeah	2.31%	3.81%	3.60%	1.11%	2.38%	3.07%
Milwaukee	3.53%	3.43%	2.67%	2.37%	2.08%	2.17%
Minneapolis-St. Paul	3.52%	4.03%	4.11%	2.04%	2.30%	3.47%
Nashville	4.08%	4.72%	4.01%	2.05%	2.34%	3.13%
New Orleans	2.72%	3.90%	2.60%	1.33%	2.25%	2.00%
New York-Northeastern NJ	2.49%	3.33%	3.06%	1.65%	2.34%	2.70%
Norfolk	4.89%	3.68%	4.25%	3.49%	2.05%	3.65%
Oklahoma City	3.78%	3.91%	4.79%	2.42%	2.31%	4.20%
Omaha	3.33%	2.93%	2.51%	2.21%	1.63%	2.04%
Orlando	5.30%	4.20%	5.72%	3.39%	2.00%	4.90%
Philadelphia	4.52%	4.67%	5.05%	3.29%	3.24%	4.52%
Phoenix	5.59%	5.54%	5.90%	3.40%	2.98%	4.96%
Pittsburgh	5.13%	4.26%	3.15%	3.72%	2.63%	2.56%
Portland-Vancouver	3.58%	4.79%	4.23%	1.58%	2.43%	3.37%
Providence-Pawtucket	4.63%	4.90%	3.49%	2.56%	2.48%	2.61%
Rochester	4.18%	2.91%	1.73%	2.86%	1.39%	1.18%
Sacramento	3.25%	4.42%	4.70%	1.48%	2.32%	3.93%
Salem	4.13%	3.09%	3.39%	3.26%	2.08%	3.02%
Salt Lake City	4.49%	4.38%	3.86%	2.35%	1.88%	2.94%
San Antonio	2.45%	3.07%	3.15%	1.13%	1.52%	2.58%
San Bernardino-Riverside	2.61%	4.57%	5.11%	1.00%	2.66%	4.40%
San Diego	1.27%	3.04%	4.34%	0.35%	1.95%	3.93%
San Francisco-Oakland	0.58%	3.59%	3.33%	-0.29%	2.54%	2.95%
San Jose	1.28%	2.88%	3.59%	0.34%	1.76%	3.17%
Seattle-Everett	1.85%	3.57%	4.74%	0.93%	2.48%	4.34%
Spokane	5.55%	3.58%	4.00%	4.73%	2.63%	3.65%
St. Louis	2.18%	3.87%	2.87%	0.80%	2.24%	2.27%
Tacoma	3.83%	3.54%	4.88%	3.07%	2.65%	4.55%
Tampa	6.17%	6.03%	5.68%	3.50%	2.92%	4.54%
Tucson	8.51%	7.31%	4.76%	4.41%	2.57%	3.04%
Washington DC	2.70%	4.70%	4.90%	1.05%	2.74%	4.18%
AVERAGE	**2.99%**	**3.90%**	**3.85%**	**1.64%**	**2.33%**	**3.28%**

Note: Los Angeles and San Francisco have negative growth in VMT when no lane miles are constructed, thus 100% of growth is attributed to the induced travel effect.

Table 6: Estimated Induced Travel Effect using Models 2-B, 4-B, and 4-D

Metropolitan area	*Percent of total VMT growth attributable to induced effect, Calculated with reduced form model 2-B.*	*Percent of total VMT growth attributable to induced effect. Calculated with instrumental variable model 4-B*	*Percent of total VMT growth attributable to induced effect. Calculated with instrumental variable model 4-D.*	*Trend annual growth in Lane Mile capacity*
Albany-Schenectady-Troy	11.19%	25.20%	8.48%	0.59%
Albuquerque	51.23%	53.38%	24.52%	3.25%
Allentown-Bethlehem-Easton	30.70%	38.55%	17.12%	2.30%
Atlanta	69.24%	52.85%	18.00%	3.84%
Austin	67.09%	65.59%	27.96%	5.32%
Bakersfield	24.58%	43.19%	17.55%	3.20%
Baltimore	36.32%	35.88%	13.80%	1.88%
Beaumont	18.74%	33.86%	11.94%	1.58%
Boston	17.02%	19.99%	7.45%	0.95%
Boulder	22.51%	37.10%	15.68%	2.24%
Brownsville	16.94%	43.16%	11.68%	1.84%
Buffalo-Niagara Falls	7.35%	15.32%	6.44%	0.61%
Charlotte	35.70%	44.20%	13.02%	2.76%
Chicago-Northwestern IN	47.12%	45.16%	24.61%	2.76%
Cincinnati	42.87%	38.11%	13.86%	1.37%
Cleveland	30.05%	30.42%	13.07%	1.17%
Colorado Springs	18.62%	34.12%	10.53%	1.86%
Columbus	35.06%	32.64%	11.90%	1.37%
Corpus Christi	33.42%	54.49%	22.57%	2.40%
Dallas	47.34%	37.19%	11.97%	1.59%
Denver	27.11%	30.79%	8.20%	1.16%
Detroit	48.13%	37.85%	21.25%	1.67%
El Paso	17.95%	28.12%	8.73%	1.30%
Eugene-Springfield	16.56%	34.16%	9.59%	0.96%
Fort Worth	49.31%	48.11%	20.75%	2.05%
Fresno	12.43%	23.90%	6.41%	1.06%
Ft. Laud.-Hollywood-Pomp. Bch	33.84%	40.73%	13.27%	2.17%
Harrisburg	40.09%	41.87%	19.77%	2.36%
Hartford-Middletown	33.29%	38.86%	14.79%	2.10%
Honolulu	51.03%	33.78%	14.00%	1.86%
Houston	70.10%	50.07%	20.50%	2.97%
Indianapolis	50.24%	49.33%	20.30%	1.95%

Jacksonville	37.81%	47.04%	17.68%	2.80%
Kansas City	35.83%	41.47%	15.78%	1.94%
Laredo	35.89%	63.77%	28.34%	4.69%
Las Vegas	31.58%	44.41%	11.24%	2.94%
Los Angeles	100.00%	30.69%	9.82%	1.17%
Louisville	76.71%	60.41%	34.29%	2.80%
Memphis	40.11%	51.18%	19.67%	3.06%
Miami-Hialeah	52.19%	37.62%	14.60%	1.85%
Milwaukee	32.83%	39.48%	18.49%	1.75%
Minneapolis-St. Paul	41.89%	42.95%	15.50%	2.24%
Nashville	49.68%	50.50%	21.76%	3.09%
New Orleans	51.12%	42.18%	22.95%	2.13%
New York-Northeastern NJ	33.80%	29.75%	11.84%	1.28%
Norfolk	28.77%	44.25%	14.13%	2.11%
Oklahoma City	35.99%	40.80%	12.32%	2.06%
Omaha	33.52%	44.41%	18.90%	1.69%
Orlando	35.93%	52.46%	14.37%	2.86%
Philadelphia	27.07%	30.68%	10.45%	1.83%
Phoenix	39.11%	46.13%	15.98%	3.29%
Pittsburgh	27.34%	38.21%	18.74%	2.10%
Portland-Vancouver	55.83%	49.27%	20.41%	3.05%
Providence-Pawtucket	44.65%	49.42%	25.23%	3.13%
Rochester	31.50%	52.27%	31.87%	1.99%
Sacramento	54.57%	47.54%	16.47%	2.72%
Salem	21.15%	32.76%	10.97%	1.31%
Salt Lake City	47.73%	57.13%	23.78%	3.26%
San Antonio	53.84%	50.57%	18.11%	2.02%
San Bernardino-Riverside	61.50%	41.82%	13.82%	2.46%
San Diego	72.56%	36.05%	9.38%	1.42%
San Francisco-Oakland	100.00%	29.12%	11.45%	1.35%
San Jose	73.55%	38.78%	11.50%	1.45%
Seattle-Everett	49.73%	30.71%	8.57%	1.42%
Spokane	14.81%	26.38%	8.68%	1.22%
St. Louis	63.24%	42.24%	20.74%	2.12%
Tacoma	19.84%	25.07%	6.74%	1.14%
Tampa	43.24%	51.64%	20.15%	4.01%
Tucson	48.23%	64.81%	36.03%	6.14%
Washington DC	61.05%	41.83%	14.78%	2.53%
AVERAGE	**45.16%**	**40.23%**	**14.94%**	**1.95%**

Figure 1

Relationship Between Current Lane Mile Growth and Induced Travel Effect